AI-based Heart Disease Prediction and Time Series Forecasting

System Documentation

Somesh Gupta (20817245)
Ankita Kapoor (20811694)
Michael Lynch (20852964)
Shadman Raihan (20858688)
Nitheesha Reddy Penta Reddy (20811504)

Overview

- This project is a web application that uses machine learning to analyze the UCI heart disease dataset and make predictions based on supplied medical data.
- The website should display the risk factors to the user as well as a probability or confidence score of their health in the coming years. If possible, the lifestyle choices to be made should also be displayed.

Link to our Website: http://35.196.37.255/

DEVELOPMENT

For development, we followed the Agile Model and attempted to incorporate continuous integration and deployment. We held weekly meetings and kept in touch using the Slack IM platform, as well as Skype calls when necessary. Tasks were initially divided up using Basecamp although towards the end of the project we started using Gitlab issues and milestones to track progress.

Testing was initially done manually, although automated tests were eventually written in Pytest, with Docker and Docker-Compose being used to set up the test environment. A completely automated CI/CD pipeline was attempted but was unsuccessful due to architectural choices made early in the project. The benefits of test-driven development became apparent towards the end of the project and in retrospect would have been much easier to implement at the beginning.

For version control, we used git and synced our project with a repository hosted on the University's GitLab server. The protected master branch was used for the most recent stable version to be deployed, a 'dev' branch was set to the most recent development awaiting testing and various sub-

branches were created for individual tasks. This approach ensured that the code was developed in an organized fashion and always had a working instance available to quickly revert to.

There are 3 main modules in our project which are as follows:

1) Machine Learning:

❖ Data:

The dataset is an aggregate of the following raw files-

- 1. Cleveland Clinic Foundation (cleveland.data)
- 2. Hungarian Institute of Cardiology, Budapest (hungarian.data)
- 3. V.A. Medical Center, Long Beach, CA (long-beach-va.data)
- 4. University Hospital, Zurich, Switzerland (switzerland.data)

Total: 1000 Data-points

Features: 76 (including the target variable)

Target Variable: Goal [it is integer-valued from 0 (no presence) to 4]

The data was initially accessed on Kaggle although a more complete instance of the dataset was found on the UCI server at https://archive.ics.uci.edu/ml/datasets/Heart+Disease. The data was initially in a raw format with no labels, although text files with documentation were available which enabled cleaning and reconstruction. Formatting errors in the dataset resulted in about 70 data points being unusable, and these were discarded.

The data was loaded into a pandas data frame format and manually labeled, then the four datasets were merged into one and the data was saved in CSV format for portability.

The labeling script also printed out information on the dataset, such as further explanations of the labels.

After feature selection we got:

Features: **15** ['cp', 'thalach', 'oldpeak', 'rldv5e', 'ladprox', 'laddist', 'cxmain', 'ramus', 'om1', 'rcaprox', 'rcadist','age','sex','chol','target'] (including the target variable)

Attribute documentation:

```
age
sex
chol: serum cholestoral in mg/dl
cp: -- Value 0: no chest pain
  -- Value 1: typical angina
  -- Value 2: atypical angina
  -- Value 3: non-anginal pain
```

-- Value 4: asymptomatic

thalach: maximum heart rate achieved

oldpeak: ST depression induced by exercise relative to rest

rldv5e: height at peak exercise

ladprox: Proximal Left Anterior Descending Artery
laddist: Distal Left Anterior Descending Artery

cxmin: Main Circumflex Artery

ramus: Ramus Intermedius Coronary Artery

om1: First Obtuse Marginal

rcaprox: Proximal Right Coronary Artery
rcadist: Distal Right Coronary Artery

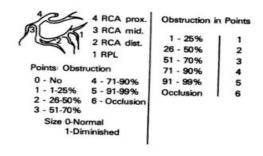


FIGURE 1 Evaluation of coronary angiographic data. RCA prox. = Proximal right coronary artery RCA mid. = Middle right coronary artery RCA dist. = Distal right coronary artery RPL = Right posterior lateral artery.

Target Variable: Target [Class 0= Low Risk of Heart disease and Class 1= High risk of Heart disease] after mapping 2,3,4 values to 1 in the target from those 4 datasets.

***** Tools and Technologies:

Libraries such as - NumPy, pandas, Scikit-Learn, Matplotlib, seaborn

Process followed:

1) In our dataset, we have the target variable that is fairly distributed with the count of around 400 for 'people with no heart disease' and 600 for 'people with heart disease'

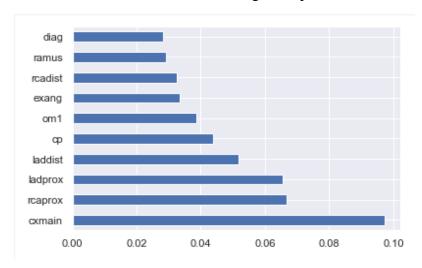
2) Feature Selection-

• Split data into train 80% and test 20%.

• Applied 'Random Forest Classifier' with n_estimators = 10

3) Feature Importance-

- We can get the feature importance of each feature of your dataset by using the feature importance property of the model.
- Feature importance gives us a score for each feature of your data, the higher the score more important or relevant is the feature towards our output variable.
- Feature importance is an inbuilt class that comes with Tree-Based Classifiers, we used Extra Tree Classifier for extracting the top 10 features for the dataset.



Plot graph of feature importances for better visualization

4) Recursive feature elimination (RFE) with random forest-

- It uses one of the classification methods (random forest in our example), assigns weights to each of the features whose absolute weights are the smallest are pruned from the current set features. That procedure is recursively repeated on the pruned set until the desired number of features.
- Choosing the top 10 features using the RFE method.

5) Recursive feature elimination with cross-validation and random forest-

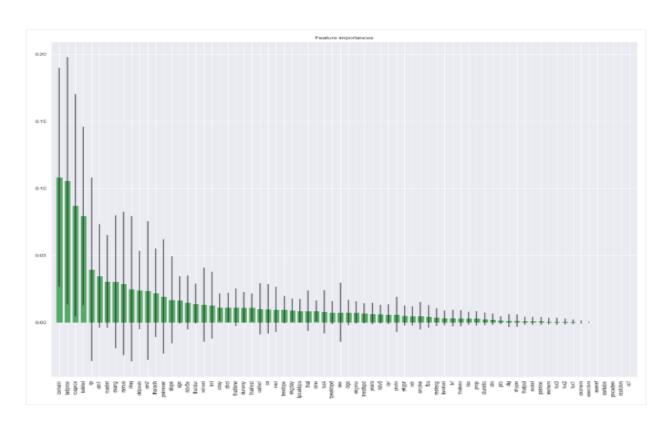
- Finding the optimal number of features using the RFE with cross-validation.
- Output:

Optimal number of features: 11

Best features: Index(['cp', 'thalach', 'oldpeak', 'rldv5e', 'ladprox', 'laddist', 'cxmain', 'ramus', 'om1', 'rcaprox', 'rcadist'], dtype='object')

6) Tree-based feature selection and random forest classification-

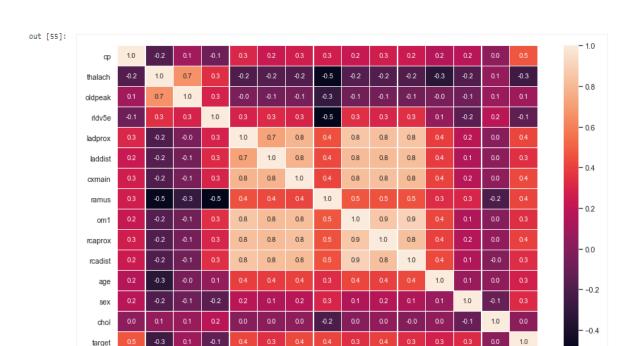
• In the random forest classification method, there are a feature important attributes that are the feature importances (the higher, the more important the feature). To use the feature_importance method, in training data there should not be correlated features. The random forest chooses randomly at each iteration, therefore the sequence of feature importance list can change.



Feature Ranking Curve

7) Feature Extraction-

- We used PCA, Kernal PCA as well as t-SNE but we were not able to segregate our data points.
- So instead of this we selected few important features from all the other above mentioned analysis. Those 15 features including the target are: [['cp', 'thalach', 'oldpeak', 'rldv5e', 'ladprox', 'laddist', 'cxmain', 'ramus', 'om1', 'rcaprox', 'rcadist','age','sex', 'chol','target']



Correlation(heatMap) for the selected features

ramus

ladprox laddist cxmain

8) Classification Algorithms:

thalach oldpeak rldv5e

• On these final set of features, we applied 4 classification algorithms and got the following accuracy scores:

chol

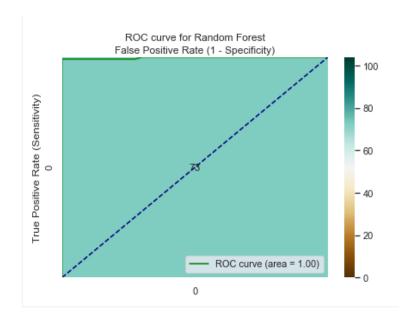
Algo	Acc. Score(in
	%)
Random Forest	98.33
KNN	67.22
Decision Tree	96.67
Naïve Bayes	70

- We also applied a boosting technique i.e AdaBoostClassifier which gave the same accuracy as obtained by the Random Forest which is assumed to be the best.
- So we chose the Random Forest classifier for our model which gave the highest accuracy of 98.33%.

Confusion Matrix for Random Forest:



ROC curve for Random forest:



9) Time Series: [Future Work]

Initially, our idea was when a patient enters his data into the website, our website should predict the risk of having heart disease as well as forecast his/her future risk based on the data he/she has entered. When we have finished the analysis, to forecast a future, the history of the patient is needed but the UCI website doesn't have the history of the data. So we have pushed this concept for future work and is still in the development phase. Currently, when the same patient enters his data, his time series of data is stored in the database. From that data provided by the user, we have forecasted their future using ARIMA/SARIMA model for now which is a continuous process.

2) Back-end and Integration:

Tools and Technologies:

For Backend: Flask tool is used which is a micro-web framework→libraries used are

render_template, Requests, URL_for, Redirect

For Database: Pymongo is used which is a server-based database.

For Integration: used Docker

For Deployment: used the Amazon and Google cloud platforms (AWS and GCP)

❖ Process Followed:

Back-end: We created a Landing page in which we implemented the fields. Then a database is created. Data given by the user is stored in the database and that data from the database is fetched and provided to the machine learning model. The model then returns a value on which the prediction is done. The value returned can be either 0 or 1, where 0 denotes that 'the user is having a low risk of heart disease' and 1 denotes that 'the user is having a high risk of heart disease'

Integration:

- We used Docker to containerize the components of the web application and dockercompose for orchestration Containerizing the application allowed a standard development environment and easy integration with cloud platforms for deployment.
- An attempt to deploy the web application using Kubernetes on GKE was unsuccessful due to configuration errors between GitLab and Google. The error was not resolved before the end of the project and would likely need to be debugged by starting from scratch.
- The deployment on GKE integrated with a GitLab build pipeline which reported on the status of the project after each push to the remote repository although due to the previously mentioned errors, this did not work. However, transitioning to a full CI/CD model would have made the project proceed much more quickly.

3) Front-end:

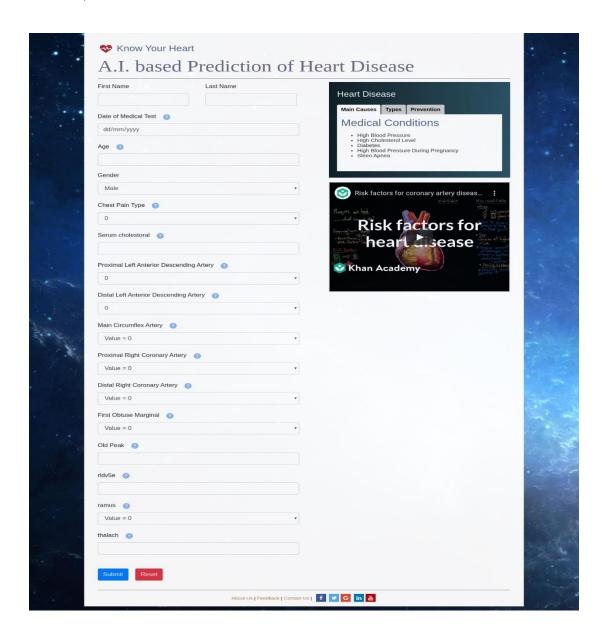
❖ Tools and technologies: HTML, CSS, JAVASCRIPT, BOOTSTRAP

Process Followed:

User Interface: There are three main pages:

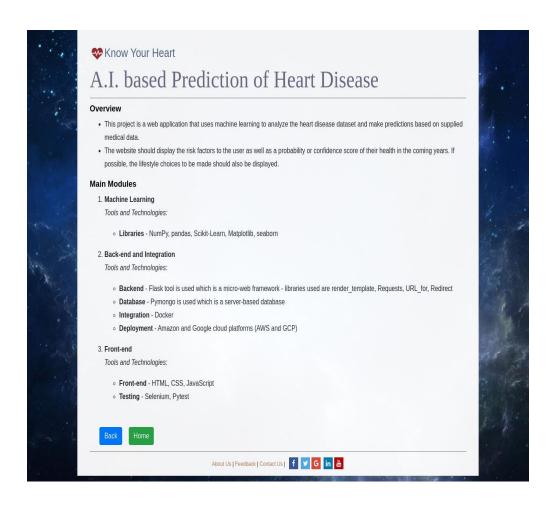
1) Home page/ Landing page:

Fields: On this page, the user will enter his details. There are 17 fields in total which all are mandatory. Out of 17 fields, 14 are the important features found from the data analysis and the other 3 are just the basic information which includes First Name, Last Name, and Date on which the user enters the details and checks his result.

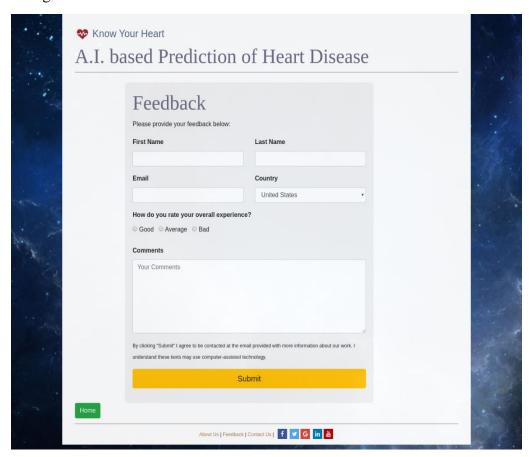


There are three links (About Us | Feedback | Contact Us) on the footer as well as social media links four our website.

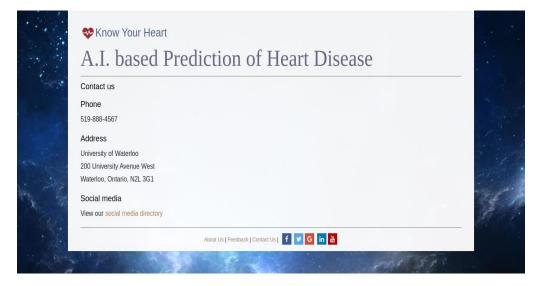
About Us page: Describes the overview of our website.



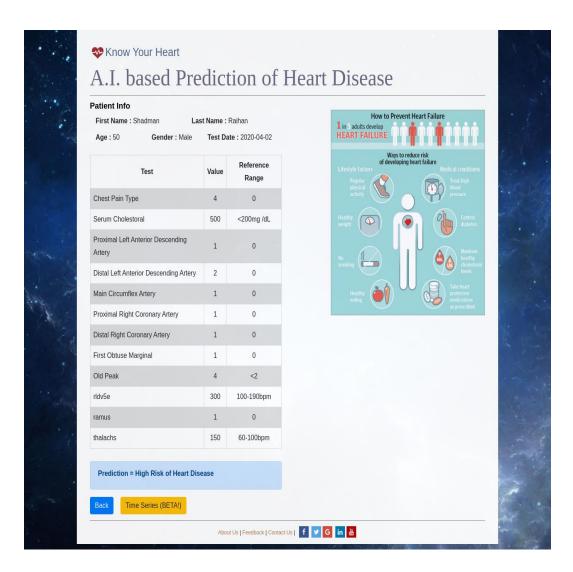
Feedback page: Where users can give feedback related to our work/website. There are certain fields that he has to enter while giving feedback which includes the Overall Rating and Comments section as well.



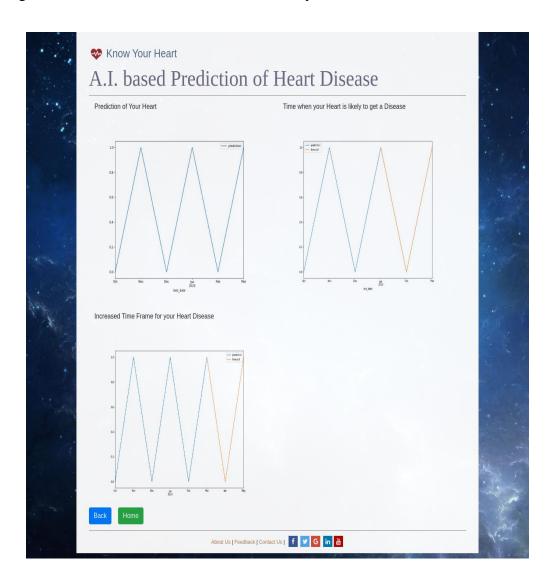
Contact Us page: This provides the details like contact number, address, etc. so that users can easily reach us.



2) **Result Page:** This page shows the results predicted by our website where there is High or Low risk of Heart Disease. The table shows the details of the patient and the normal range so that patient can compare his results. Also, there is a button "Time-Series BETA", by clicking it the user can open Time-Series Page.



3) Time-Series Forecasting Page: This page is under construction. For now, the graphs are generated by using dummy data of a patient. Basically, it provides the future predictions of a patient over a period of time like the time when your heart is likely to get a disease and an increased time frame of your heart disease.



TESTING

Tools and technologies:

Used Pytest framework for unit testing → a testing framework that allows us to write test codes using python. We can write code to test anything like database, API, even UI if we want. Basically, we used it for unit testing.

Used Selenium framework for integration testing → a portable framework for testing web applications. Selenium provides a playback tool for authoring functional tests without the need to learn a test scripting language.

Used bandit for Security testing

Process Followed:

Unit Testing and Integration Testing

- Tests were written in the Pytest and mostly focused on the web application interface, using GET and POST requests to verify that the correct web page was served in response to the user request. These acted as unit tests for the various web application rendering functions and also as a system test ensuring that the application was up and able to take user input, as well as read and write to the database.
- For automated testing, we used the selenium framework.

Security Testing

For common security-related testing for our Website, we have used Bandit which
is a python based tool that gives common security flaws in the software. Using this
tool we were able to eliminate a few security-related issues that appeared while
testing our code using Bandit and were able to successfully remove critical issues
from our main code files.

```
| Same | Decision | Part | Par
```

Severity of Risk: High

```
Charlo | Timp profile Include tests: None | Canal | Timp profile Include tests | Timp profi
```

Severity of Risk: Medium [Pickle and module that wrap it can be unsafe]

This issue would not affect our Website that much because for now, it is a small-scale project and we are using Pickle for just prediction. If in any worst-case any unknown activity happens, we will get notified.